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Regional R&D Efficiency in Korea from Static and Dynamic Perspectives

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ABSTRACT

R&D efficiency has gained great attention in regional innovation. This study examines the R&D efficiency patterns of Korean regions for 2005–2009 from static and dynamic perspectives. This study employs data envelopment analysis to identify the regions' R&D performances relative to the best practices from the static perspective, and the Malmquist Productivity Index to evaluate their dynamic changes within a given timeframe. The results classify Korean regions into the deteriorating, lagging, and improving groups and indicate that most regions suffer from declining R&D productivity over time because of the inability of catching up with the best practices. To improve the catch-up effect, this study suggests (1) implementing exploitative strategies including direct technical imports and complementary R&D, (2) growing the number of government research institutes on a regional scale, and (3) increasing the ratio of industrial R&D organisations relative to industrial R&D expenditures are recommended.

Keywords: regional R&D efficiency, Korea, Data Envelopment Analysis, Malmquist Productivity Index

INTRODUCTION

Regional innovation initiatives aim to bridge the innovation-based economic gap between heterogeneous regions and strengthen their innovation competitiveness on a national scale (OECD, 2008). The European Union (EU; 2006) highlights the role of research and development (R&D) in regional innovation. Some studies have attempted to evaluate regional innovation performance to determine the evidence-based policy implications of regional initiatives (e.g. AUTIO, 1998; DIEZ, 2001; EVANGELISTA *et al.*, 2001). However, it is difficult to compare interregional innovation performance, as R&D is not conducted under identical conditions owing to an imbalanced distribution of R&D capabilities across different regions (FELDMAN, 1994). Thus, the approach to simply analyse an absolute performance aspect, such as the number of R&D outputs, is inappropriate, because it does not consider the maximum attainable performance level for each region (BOSCO and BRUGNOLI, 2010). The study of R&D efficiency has gained substantial attention in recent years as researchers need to also consider resource accessibility in the assessment of heterogeneous regional R&D processes. Between 1993 and 2012, the keywords ‘R&D efficiency’, ‘research and development efficiency’, and ‘research efficiency’ appeared in a number of academic journal papers¹. Despite the abundance of literature on regional efficiency evaluation (e.g. BAI, 2013; CHEN and GUAN, 2012; FRITSCH and SLAVTCHEV, 2011; GUAN and CHEN, 2010; ZABALA-ITURRIAGAGOITIA *et al.*, 2007), very few studies examine this issue from a dynamic perspective (ARCHIBUGI *et al.*, 1999). Moreover, because a region’s R&D efficiency can change over time, the longitudinal investigation of R&D efficiency can help assess the extent to which a region demonstrates consistency in productivity.

Despite rapid economic growth, Korea’s nation-wide approach to innovation resulted in economic disparities between the capital metropolitan areas (Seoul, Gyeonggi, and Incheon) and other areas (DUKE *et al.*, 2006). Consequently, Korea began to adopt regional innovation frameworks in the mid-1990s to reduce interregional economic imbalances and reinforce competitiveness (CHUNG, 2002). Further, the Roh Moo-hyun administration (2003–2008) enacted the so-called “Special Law on Decentralisation” and “Special Law on the Construction of New Administrative Capital” in 2003 and the “Special Law on Balanced National Development” in 2004 to promote regional innovation. Since 2008, the Lee Myung-bak administration has aimed to strengthen regional science and technology competitiveness through R&D investment and efficiency endeavours such as the “Third Regional Science and Technology Promotion Plan” (2008–2013) and the “Five-year Comprehensive

¹ According to the results of an on-line search (<http://www.sciencedirect.com>), 889 journal papers were published with these keywords.

Regional Science and Technology Promotion Plan” (2009–2013) (MINISTRY OF EDUCATION, SCIENCE AND TECHNOLOGY [MEST], 2010a). A study of Korean regions can provide valuable insights for policy-making related to regional R&D systems transitioning from the national to the regional level, particularly where both approaches coexist.

This study aims to contribute to the literature on regional innovation by quantifying the respective R&D efficiencies of Korean regions from static and dynamic perspectives. Korea is primarily characterised by dirigiste initiatives (BRACZYK *et al.*, 1998), which are congruous with regionalised national approaches (ASHEIM and ISAKSEN, 1997) in a top-down manner (HOWELL, 1999). Consequently, it is worthwhile to examine the interregional differences in R&D efficiency from an intra-national perspective. Although regional innovation initiatives were introduced in Korea in the 1990s, the Korean government began to provide region-wide R&D data only recently. Thus, this study employs data only for the period from 2005 to 2009.

The next section provides a brief explanation of the regional knowledge production process. The third section introduces the DEA and MPI methods for the evaluation of regional R&D efficiency. The fourth section describes the data used in this study. The fifth section presents the empirical findings, followed by a discussion of the results in the sixth section. The last section concludes the paper with a summary of the main results, the limitations of the study, and directions for future research.

REGIONAL KNOWLEDGE PRODUCTION PROCESS

An innovation system is an aggregate of the knowledge production processes in an innovation environment (ASHEIM and ISAKSEN, 1997). A linear knowledge production function is based on the premise that the innovation process entails a linear relationship between inputs and outputs (ACS *et al.*, 2002; GODIN and GINGRAS, 2000; GRILICHES, 1990; HESSELS and VAN LENTE, 2008; PATRICK, 2002; TSAO *et al.*, 2008; ZABALA-ITURRIAGAGOITIA *et al.*, 2007). Universities, industries, and government research institutes (GRIs) are the key R&D actors in the process of any knowledge economy (ETZKOWITZ, 2008). A regional knowledge production function includes universities, industries, and GRIs that consume R&D inputs (e.g. people, money, knowledge) to produce new regional scientific and technological knowledge (e.g. patents, papers) (OECD, 1996; ZABALA-ITURRIAGAGOITIA *et al.*, 2007; see Figure 1).

<Insert Figure 1.>

Figure 1 demonstrates that a simple regional knowledge production function can be seen as a result of R&D inputs, process, and outputs. Primary R&D inputs are obtained from either internal or external sources of the respective R&D performing units. Thus, regardless of the sources (in-house sources, government, etc.) or R&D actors (universities, industries, or GRIs), a linear approach for evaluating the regional knowledge production process accounts for the total volume of regional R&D inputs consumed in the process to produce the total volume of regional R&D outputs. In other words, a region's total R&D input level is the sum of resources invested by the universities, industries, and GRIs within the region that is transformed into outputs.

The degree to which these regions' knowledge production processes are efficient can be evaluated from either static or dynamic perspectives. Static efficiency reflects the relative positions of regions using the best practices as defined by efficient regions (CHARNES *et al.*, 1994). Dynamic efficiency accounts for time-dependent changes in regional positions relative to those best practices, that is productivity increase or decrease (FÄRE *et al.*, 1994). It can be perceived that the regions' relative positions are determined by an interregional comparison in terms of static and dynamic R&D efficiency, both of which consider the respective efficiencies of each region and other comparative regions (i.e. best practices). For example, an inefficient region can improve its relative (static) position if it exhibits increasing productivity, until it (possibly) becomes efficient. In contrast, if a currently static efficient region shows decreasing productivity, then the region would fall behind other comparative regions over time.

Considering the patterns of both static and dynamic efficiencies, regions can be allocated in the matrix displayed in Figure 2.

<Insert Figure 2.>

The leading group (top-right quadrant) represents an ideal situation in which the regions are both R&D efficient and register an increasing R&D productivity. If these leading regions can maintain their R&D productivity increase, then they would likely face a future characterised as consistently efficient, in both a static

and dynamic sense. The deteriorating group (top-left quadrant) is (still) efficient, but suffers from a decreasing productivity over time. Although deteriorating regions are efficient at present, they are likely to lose this position over time due to their decreasing R&D productivity. The lagging group (bottom-left quadrant) is not only inefficient, but also has decreasing productivity. Therefore, the lagging group faces the greatest problems in terms of efficiency patterns; lagging regions are expected to continue their downward trend towards further inefficiency. The improving group (bottom-right quadrant) contains regions that though currently inefficient, but have increasing productivity. These regions can possibly become leading regions if they are able to maintain this productivity increase over time.

Based on the notions outlined above, this study analyses Korean regions' relative positions defined by R&D efficiency patterns. The following section explains the methodology this study employed to analyse these efficiency patterns.

METHODOLOGY

This study employs data envelopment analysis (DEA) and the Malmquist Productivity Index (MPI) to determine R&D efficiency patterns of Korean regions. Because MPI (FÄRE *et al.*, 1994) is a DEA-based technique, these two methods share common strengths in terms of R&D efficiency evaluation. Commonly used ratio analysis cannot accommodate multiple inputs and outputs (SHERMAN, 1985). However, both the DEA and MPI can handle multiple input- and output variables with different units of measurement (CHARNES *et al.*, 1994). Moreover, unlike statistical methods such as a regression model, non-parametric approaches do not require a specified production function to link inputs with outputs (BERGER and HUMPHREY, 1997). This is relevant in the evaluation of a complex issue such as R&D efficiency, particularly in terms of studying the conversion of R&D inputs into outputs, where true production function is unknown and assumptions related to the nature or shape of the relationship between inputs and outputs cannot be easily justified. DEA allows the observed data to speak for itself by letting a convex envelopment of observations provide a conservative estimate of the frontier of the production possibility set, based on very few assumptions. This is also an advantage relative to other methods, like Stochastic Frontier Analysis (see e.g. AIGNER *et al.*, 1977), which requires assumptions not only on the functional form of production function (although some variations are quite flexible), but also the shape of the inefficiency distribution. However, the advantage of needing only few

assumptions in DEA comes at the price of statistical properties. DEA efficiency analysis can be criticised for its bias from a statistical perspective, as it uses small samples (SIMAR and WILSON, 2000). Nevertheless, the use of few input and output variables can overcome issues related to sample size (DYSON *et al.*, 2001).

In a precise way, different regions may possess distinct industrial structures and R&D stages that lead to different quality of R&D outcomes. However, a regional R&D system is the meso- or macro-level mixture of diverse knowledge production processes (ASHEIM and ISAKSEN, 1997) that are upon on various R&D actors including universities, industries, and GRIs (ETZKOWITZ, 2008). The meso- or macro-level knowledge production process the aggregated transducer that converts R&D inputs into a set of far-ranging region-wide knowledge base. Therefore, in a broad way, R&D outputs produced in different regions are perceived as comparable in this paper.

On the basis on the above methodological strengths and the comparability of outputs, DEA and MPI are suitable to evaluate R&D efficiency and its time-based change of regions.

Data envelopment analysis

DEA is a linear programming technique that evaluates the performance of decision-making units (DMUs) relative to an efficiency frontier set on the basis of efficient DMUs (CHARNES *et al.*, 1994; COOPER *et al.*, 2007). Methodologically, DEA and MPI can be utilised in either a constant returns-to-scale model (the Charnes, Cooper, Rhodes [CCR] model) (CHARNES *et al.*, 1978) or a variable returns-to-scale model (the Banker, Charnes, Cooper [BCC] model) (BANKER *et al.*, 1984). Compared to a BCC model, a CCR model provides better discrimination among DMUs (PODINOVSKI and THANASSOULIS, 2007). Moreover, the BCC model is not well suited for measuring the change in total factor productivity (GRIFELL-TATJÉ and LOVELL, 1995). Consequently, this study employs a CCR-DEA model to discriminate the Korean regions more clearly. Further, this study adopts an input-oriented approach that aims to minimise inputs for a given level of output in order to reach the efficiency frontier, as macro-level systems (i.e. regions in this paper) cannot easily control the level of output.

This study uses two methods to calculate DEA scores: the super-efficiency DEA scores for a static regional R&D efficiency assessment, and the standard DEA scores for MPI score calculation. Many researchers

have assumed that an R&D input-output transformation process involves a time delay. The average length of the delay varies according to industry (GOTO and SUZUKI, 1989) and R&D actors (ADAMS and GRILICHES, 2000; GUELLEC and VAN POTTELSBERGHE DE LA POTTERIE, 2004). However, the empirical influence of time delay on efficiency is not substantial (GRILICHES 1990; HOLLANDERS and CELIKEL-ESSER, 2007) and its length is not definite (WANG and HUANG, 2007). Therefore, this study simply defines an input-output time delay as one year (i.e. inputs from 2005 and outputs from 2006, etc.).

To assess the static regional R&D efficiency for the period from 2005–2009, this study considers super-efficiency DEA scores, developed by Andersen and Petersen (1993). These are calculated by excluding each efficient region from the reference group in the model that is used to evaluate its efficiency. Super-efficiency scores can be used to rank regions (ZHU, 2009) as they facilitate a discrimination of the efficient DMUs, all of which get an efficiency score of 1 in the standard DEA. The super-efficiency scores for efficient DMUs are equal to or higher than 1; their values represent the degree to which the DMUs can increase their inputs and still remain efficient. For the static super-efficiency DEA model, the variable values for a region are aggregated across the five years under analysis. Thus, to account for the time delay outlined above, the input for a region is the sum of input values from 2005 to 2009 and the output is the sum of values from 2006 to 2010. x_{ij} is the aggregated level of input i used by region j from 2005 to 2009, where $i = 1, \dots, m$ is the number of inputs and $j = 1, \dots, n$ is the number of regions. Similarly, y_{rj} is the aggregated level of output r produced by region j from 2006 to 2010, where $r = 1, \dots, s$ is the number of output factors. An observation in this analysis is given by the vector of (m) inputs and vector of (s) outputs, $(X, Y) \in R^{m+s}$, where the input and output values are aggregated over the years 2005–2009 and 2006–2010, respectively.

The static input-oriented super-efficiency CCR-DEA score for DMU $j'(X_{j'}, Y_{j'})$ is defined as follows:

$$\begin{aligned} \theta_{j'}^{super} &= \min \theta \\ \text{subject to } \sum_{\substack{j=1 \\ j \neq j'}}^n \lambda_j x_{ij} &\leq \theta x_{ij'} \quad i = 1, 2, \dots, m; \\ \sum_{\substack{j=1 \\ j \neq j'}}^n \lambda_j y_{rj} &\geq y_{rj'} \quad r = 1, 2, \dots, s \end{aligned}$$

$$\lambda_j \geq 0, \quad (1)$$

where λ_j is the weight of observation for (region) j in the benchmark for observation j' , and $\theta_{j'}^{super}$ is greater than 1 if region j' is efficient and smaller than 1 if the region is inefficient.

Standard DEA scores are used to estimate MPI scores (FÄRE *et al.*, 1994). For the MPI, this study considers changes in R&D productivity of each Korean region between the two extreme years (i.e. between 2005–2006 and 2009–2010). Changes in productivity signified by the MPI scores can be decomposed into a shift in the efficient frontier between 2005 (outputs from 2006) and 2009 (outputs from 2010) and the changes in the regions' efficiencies relative to the frontiers in the two years. Let x_{ij}^t denote the level of input i used by region j in the year t , with $t=2005, 2009$ and let y_{rj}^{t+1} be the level of output r produced by region j in year $t+1$. An observation is now given by the vector of (m) inputs in the year t and the vector of (s) outputs in year $t+1$, $(X^t, Y^{t+1}) \in R^{m+s}$.

The input-oriented CCR-DEA score for DMU j' ($X_{j'}^t, Y_{j'}^{t+1}$) relative to the frontier for time period t^* (inputs from t^* , outputs from t^{*+1}) is defined as follows:

$$\begin{aligned} \theta^{t^*}(x_{j'}^t, y_{j'}^{t+1}) &= \min \theta \\ \text{subject to } \sum_{j=1}^n \lambda_j x_{ij}^{t^*} &\leq \theta x_{ij}^t, \quad i = 1, 2, \dots, m \\ \sum_{j=1}^n \lambda_j y_{rj}^{t^{*+1}} &\geq y_{rj'}^{t+1}, \quad r = 1, 2, \dots, s \\ \lambda_j &\geq 0 \quad j = 1, 2, \dots, n \end{aligned} \quad (2)$$

Malmquist Productivity Index

The MPI (CAVES *et al.*, 1982; MALMQUIST, 1953) is used to measure changes in regional R&D productivity over time (COOPER *et al.*, 2007). Methodologically, it is calculated from the standard DEA scores defined in (2) above. The MPI model employed in this study is as follows:

$$\begin{aligned}
& MPI\left(x_{j'}^{05}, y_{j'}^{06}, x_{j'}^{09}, y_{j'}^{10}\right) \\
&= \frac{\theta^{09}\left(x_{j'}^{09}, y_{j'}^{10}\right)}{\theta^{05}\left(x_{j'}^{05}, y_{j'}^{06}\right)} \times \left[\frac{\theta^{05}\left(x_{j'}^{09}, y_{j'}^{10}\right)}{\theta^{09}\left(x_{j'}^{09}, y_{j'}^{10}\right)} \frac{\theta^{05}\left(x_{j'}^{05}, y_{j'}^{06}\right)}{\theta^{09}\left(x_{j'}^{05}, y_{j'}^{06}\right)} \right]^{1/2}, \quad (3)
\end{aligned}$$

where $MPI(x_{j'}^{05}, y_{j'}^{06}, x_{j'}^{09}, y_{j'}^{10})$ represents the change in R&D productivity between 2005 and 2009 for region j' . $MPI(x_{j'}^{05}, y_{j'}^{06}, x_{j'}^{09}, y_{j'}^{10}) > 1$ indicates an increase in productivity between 2005 and 2009; conversely, a value lower than one implies a decrease in productivity during this period. A value of one indicates no change in productivity. Furthermore, model (3) can be decomposed into a technical efficiency change index (TECI) and a technical change index (TCI).

$$TECI\left(x_{j'}^{05}, y_{j'}^{06}, x_{j'}^{09}, y_{j'}^{10}\right) = \frac{\theta^{09}\left(x_{j'}^{09}, y_{j'}^{10}\right)}{\theta^{05}\left(x_{j'}^{05}, y_{j'}^{06}\right)} \quad (4)$$

$$TCI\left(x_{j'}^{05}, y_{j'}^{06}, x_{j'}^{09}, y_{j'}^{10}\right) = \left[\frac{\theta^{05}\left(x_{j'}^{09}, y_{j'}^{10}\right)}{\theta^{09}\left(x_{j'}^{09}, y_{j'}^{10}\right)} \frac{\theta^{05}\left(x_{j'}^{05}, y_{j'}^{06}\right)}{\theta^{09}\left(x_{j'}^{05}, y_{j'}^{06}\right)} \right]^{1/2}, \quad (5)$$

The TECI model (4) indicates whether a region moved closer to or further away from the efficient frontier between 2005 and 2009 (COOPER *et al.*, 2007). TECI scores reflect the catch-up effect of each region, defined by the ratio of the distances to the efficiency frontier. If one region is more capable of utilising knowledge production technologies than others, its R&D productivity would improve faster than that of other regions. Consequently, the region's distance from the frontier would decrease over time; otherwise, it will increase. The TCI model (5) denotes the change in the best practice (technology) between 2005 and 2009 (COOPER *et al.*, 2007). TCI scores reflect the frontier-shift effect that is determined by efficient regions. Technological advancements due to innovation extend the frontier level, which implies an improvement in the best practices in terms of regional R&D production. Thus, with respect to R&D, a frontier shift reflects the change in a region's potential for producing knowledge at that specific time. For this study, these two components provide further information on the sources of change in regional R&D efficiency.

DATA

Sample of observations

The analyses employ Korea's regional knowledge production data. Of the sixteen administrative regions, Jeju was excluded, as it is largely a tourism-driven region, and therefore unlikely to be comparable to other territories with an advanced scientific and technological infrastructure. Among the remaining fifteen regions considered in this study, one region is a special city, six are metropolitan cities, and eight are provinces (see Table 1).

<Insert Table 1.>

Variables and data sources

In DEA and MPI assessments, the total number of observations should ideally be at least thrice that of the total number of variables (BANKER *et al.*, 1989) or twice that of the product of the number of inputs and outputs (DYSON *et al.*, 2001). However, it is preferable to include fewer variables for a better discrimination among DMUs (DYSON *et al.*, 2001). Therefore, it is necessary to determine a small number of indicators that can represent the regional knowledge production process of the fifteen Korean regions.

R&D expenditure, R&D staff, and accumulated knowledge are typical inputs that are directly consumed in the R&D process (GUAN and CHEN, 2010). While financial resources are crucial for stimulating progress in science and technology (HASHIMOTO and HANEDA, 2008; WANG and HUANG, 2007), R&D expenditure also generally includes R&D labour costs, which are already considered (WANG and HUANG, 2007) as an important input factor. Moreover, R&D expenditure may also include explicit knowledge, as R&D funding covers intellectual property rights, which enable an organisation to acquire existing codified knowledge necessary for R&D. Therefore, this study does not consider R&D staff and accumulated knowledge to be distinct inputs. The study transforms all these different inputs to the R&D process into monetary values and aggregates them into total R&D expenditures. To quantify R&D investment, this study incorporates data from

the MEST *Survey of Research and Development in Korea* for the period of 2005–2009.² Further, in order to mitigate the impact of inflation on R&D expenditures, this study converts the annual R&D expenditures into year 2010 KRWs (i.e. using the fixed base method).

As the knowledge production function relates R&D inputs to outputs that reflect scientific and technological knowledge drawn from an R&D process, it is necessary to define knowledge as the output. Knowledge can be broadly divided into two types: tacit and codified (AUDRETSCH, 1998; LISSONI, 2001). R&D staff inputs tacit knowledge and translates it into codified knowledge. It is ultimately manifested and embedded in the form of technologies, products, and/or services through knowledge externalisation (NONAKA *et al.*, 2000). Therefore, codified knowledge is considered as an output of the R&D process. Additionally, it is easier to quantify codified knowledge, which makes it more suitable for use in quantitative methods. In terms of science and technology, this knowledge codification may be revealed through patents and academic publications.

Patents are a crucial indicator of R&D output (POPP, 2005; WANG and HUANG, 2007). Patent quantity is a proxy for the achievements embedded in an R&D process (GRILICHES, 1990), which has led to its consideration as an output variable. However, unlike some previous studies that counted the number of patents granted by domestic or international property offices (FRITSCH, 2002; FRITSCH and SLAVTCHEV, 2011), this study counts the quantity of patent applications, because it is impossible to estimate the lead time between the initial application and granting of patents as required for patent examinations (THURSBY and KEMP, 2002). The Organisation for Economic Co-operation and Development (OECD) uses a fractional count method to provide statistics on Patent Cooperation Treaty (PCT) applications. This study collected region-wide information on patent applications by searching for applicants' addresses on the World Intellectual Property Organization (WIPO) website.³

Academic publications account for a large proportion of the scientific and technological output of R&D (BROWN and SVENSON, 1998; CHERCHYE and ABELEE, 2005; FURMAN *et al.*, 2002; JIMÉNEZ-SÁEZ

² Since 1963, the Ministry of Education, Science and Technology (MEST) and the Korea Institute of Science & Technology Evaluation and Planning (KISTEP) have carried out this annual survey to collect information for national science and technology policy making and R&D planning. Inspired by the OECD Frascati Manual (1993), it covers multifaceted aspects such as R&D expenditure, R&D workers, and other factors with respect to universities, industries, and government research institutes.

³ Some patent applicants do not follow the Romanisation system proclaimed in 2000, so the names of Korean regions are seen to be spelled differently in different applications. For example, names, 'Gwangju', 'Kwangju', 'Gwangjoo', and 'Kwangjoo' have been used for Gwangju.

et al., 2011; WANG and HUANG, 2007). This study utilises the Science Citation Index Extended (SCIE) and the annual *SCI Database Analysis* published by MEST, based on the Web of Science®, Thomson Reuters, to assess the quantity of papers published annually.⁴

To assess R&D outputs, this study analyses international statistics on PCT applications and SCIE journals rather than domestic data, because international patents and publications are considered superior to their domestic counterparts. For example, in contrast to international offices, the Korea Intellectual Property Office (KIPO) does not require patent applicants to include a rigid patent reference list. Therefore, domestic patented knowledge may not be of approved quality. Similarly, scientific and technological articles published in international journals may be considered of higher quality than those published in domestic journals, as they undergo a more systematic and critical review process.

Table 2 provides data on R&D expenditure adjusted for inflation as the input, and data on PCT applications and SCIE publications as outputs, considering the time delay of one year.

<Insert Table 2.>

EMPIRICAL RESULTS

R&D efficiency and its change

Table 3 presents the R&D super-efficiencies and productivity changes of the fifteen Korean regions from 2005 to 2009. In the super-efficiency model, a score greater than 1 indicates that a region is efficient, while a score below 1 indicates it is inefficient. For the MPI, a score exceeding 1 indicates an increase in a region's R&D productivity between 2005 and 2009; a score of 1 suggests no change in a region's productivity; and a score less than 1 indicates a decrease in the region's productivity.

⁴ Thomson Reuters provides access to the world's leading citation databases including the SCIE, Social Sciences Citation Index Expanded, Arts and Humanities Citation Index, and the Conference Proceedings Citation Index (Science edition, and Social Science and Humanities edition). Instead, the MEST *SCI Database Analysis* solely deals with SCIE data.

<Insert Table 3.>

As is evident from Table 3 (second column), three regions were found to be efficient in the static model (DEA super-efficiency ≥ 1), while the remaining twelve were inefficient. Seoul demonstrated the second highest efficiency (1.116) despite being the largest producer of PCT applications and SCIE publications between 2006 and 2010 (see Table 2). Despite the strong government-driven industrial relocation policies (DUKE *et al.*, 2006), Incheon (0.496) and Gyeonggi (0.406) were found to be inefficient in R&D. The last column in Table 3 demonstrates that six regions improved their R&D productivity between 2005 and 2009 (MPI > 1), and the other nine regions declined in this regard. Although Ulsan has been one of the largest industrial districts in Korea based on its *chaebol*-driven automobile, shipbuilding, and petrochemical industries since the 1970s (OH, 1996), the city experienced the most severe decrease in its R&D productivity (0.343).

Technical efficiency change and technical change

The MPI score can be broken into TECI and TCI (see models (3), (4), and (5)). While TECI reflects the extent to which a region catches up with the frontier set by efficient regions, TCI illustrates how the technological frontier is improving from the perspective of region in questions.

<Insert Table 4.>

Table 4 demonstrates that while countrywide technological innovation advanced, many regions declined in terms of R&D productivity because of decreases in technical efficiency, specifically Seoul, Daegu, Incheon, Ulsan, Gyeonggi, Chungcheongbuk, Chungcheongnam, and Gyeongsangbuk. As seen in the last row in Table 4, although in general the frontier-shift effect showed a positive contribution to R&D productivity change (1.141), the catch-up effect (0.806) was the major factor of the general decrease in R&D productivity change (0.920). This interpretation is confirmed by Kendall's coefficient of concordance test (CONOVER,

1980), a non-parametric technique to test correlations among more than two variables based on the ranking of a small sample. Table 5 illustrates that R&D productivity change strongly correlates with the catch-up effect at the 0.01 level in terms of ranking (0.924***), but not with total TCI change.⁵

<Insert Table 5.>

As regional innovation systems become mature over time, it is intuitively expected that Korean regions may suffer from stagnation in R&D productivity change. However, Table 6 indicates that while countrywide MPI (0.982) and TECI (0.947) declined and TCI (1.036) increased, regional yearly-based trends in these indicators do not capture clear recession. In large, Korean regions fluctuated in terms of MPI, TECI, and TCI during the given period.

<Insert Table 6.>

DISCUSSION: REGIONAL POSITIONS AND IMPLICATIONS

Based on the results summarised in Table 3, the Korean regions are classified into three groups: deteriorating, lagging, and improving (see Figure 3).

<Insert Figure 3.>

This classification scheme also contains the leading group (top-right quadrant), but no region was

⁵ Hereafter, Samples are fifteen regions; *** Correlation is significant at the 0.01 level (2-tailed); ** Correlation is significant at the 0.05 level (2-tailed); and * Correlation is significant at the 0.1 level (2-tailed).

categorised there. Interestingly, these results indicate that even Seoul does not belong to the leading group, but is instead categorised as a deteriorating region characterised as efficient but with decreasing productivity. Although Seoul has historically enjoyed strong support from the government and has a rich resource-laden infrastructure (DUKE *et al.*, 2006), it seems that Seoul does not effectively leverage its advantages as a capital city to increase its R&D productivity, though it is located near the borderline between the leading and deteriorating groups. In the lagging group, Gyeonggi is one of the beneficiaries of government-driven industry development (DUKE *et al.*, 2006) and was the largest R&D investor and the second largest producer of PCT applications and SCIE publications for the period from 2005 to 2009. While Gyeonggi has experienced a rapid growth in its industrial and research districts in areas adjacent to Seoul (DUKE *et al.*, 2006), the massive investment has led to neither static nor dynamic efficiency. Within the improving group, Daejeon presents an interesting case. Daejeon has the largest GRI-research complex in Korea, which was responsible for approximately 56.6% of its total R&D expenditures for the period from 2005 to 2009 (MEST, 2010b). During this time period, Daejeon had the third highest R&D expenditures among the regions, spending around 58.6% of the expenditures of Seoul but it was inefficient since the city produced merely around 28.8% of the PCT applications of Seoul. The above cases of Seoul, Gyeonggi, and Daejeon suggest that rich researchers, finance, and government support do not necessarily guarantee superior positions relative to other regions in terms of static or dynamic R&D efficiency.

Note that this paper is focused on only an intra-country comparison (i.e. comparing domestic regions in Korea) which allocates regional positions in the four-quadrant matrix. If analysis objects are compared on an international scale (i.e. comparing with cities of other nations), Korea's regional locations would change. In this paper adopting an intra-country comparison method, the absence of leading regions does not imply that no region is advanced in R&D performance. For example, as seen in Table 2, longitudinally Seoul is reported to have the greatest quantity of PCT applications and SCIE publications in Korea, and thus the city can be regarded as the most developed place in science and technology. That is, the display of regional locations does not say that Seoul's technological development lags behind the bottom-right-quadrant regions (e.g. Gwangju, Busan, etc.). Instead, Figure 3 points out that Seoul presents the lower speed of R&D productivity change relative to the bottom-right-quadrant regions between 2005 and 2009.

While TECI reflects the catch-up effect that accounts for the contribution of change in technical efficiency toward the change in productivity, TCI is frontier-shift effect that allows technical change to

contribute to changes in productivity (COOPER *et al.*, 2007). Therefore, TECI reflects a region's efficiency in utilising its existing scientific and technological knowledge in their knowledge production process, whereas TCI is the extent to which regions improve through technological innovation. In comparing the practical implications of TECI and TCI, it is evident that the catch-up effect can be improved by exploitative efforts aimed at 'refinement, choice, production, efficiency, selection, implementation and execution' to search for new applications of existing scientific and technological knowledge (MARCH, 1991: 71). In contrast, the frontier-shift effect can be achieved through exploration efforts focused on 'search, variation, risk taking, experimentation, play, flexibility, discovery, innovation' to seek new possibilities of innovation through intensive challenges (MARCH, 1991: 71). Therefore, if a region has moved away from best practices over time, it is necessary to improve its TECI score using exploitative approaches. As March (1991) indicates, the exploitative R&D refers to the use of incumbent advanced technologies to produce more knowledge in the long-term. Conversely, if a region suffers from a decline in R&D productivity resulting from a slowdown in technical change over time, its TCI score can be improved through more aggressive R&D investment in technological advancement through innovation.

As shown in Tables 4 and 5, the catch-up effect (TECI) is largely decisive for R&D productivity change (MPI) in Korean regions (with the exception of Gangwon). Therefore, to improve their respective productivities, TECI-declining regions should focus on knowledge spillover that facilitates the transfer of best practice technologies and apply them to potential production techniques. These regions should also improve their absorptive capacities through secondary R&D that allows for the capture of other organisations' new techniques or technologies (COHEN and LEVINTHAL, 1989). This would accelerate technical imports and may enhance the catch-up ability of struggling regions. That is, these typically underprivileged regions should preferably adopt less challenging strategies for incremental innovation that is coherent with absorptive capacity corresponding to the regions' traditional scientific and technological competitiveness.

What brings about cross-regional differences in the catch-up effect? The relative level of this indicator may be attributed to characteristics of localised universities, industries, and GRIs that are core R&D performers. The considerations include their organisation-specific variables such as the amount of R&D expenditure, the population of researchers, and other related composite factors (e.g. R&D expenditure per researcher in GRIs, density of R&D organisations per R&D expenditure in universities, etc.). To identify influential factors on the catch-up effect, Kendall's coefficient of concordance test is employed. As a result, the number of GRIs has a

slightly positive correlation with TECI (0.371*). Further, the test result gives a statistical account of the effectiveness of the number of R&D organisations per R&D expenditure in the industry presents a small relation with TECI (.390**) of regions. Therefore, when regions (1) induce more GRIs in the government sector and (2) try up more industrial R&D organisations under the fixed amount of R&D expenditures in the industry sector, they are expected to stimulate their ability of catching up with frontier runners. In particular, the second measure points out an interesting implication for the industrial R&D process. Kendall's coefficient of concordance test indicates that each of the variables (the number of industrial R&D organisations and the amount of industrial R&D expenditures) does not significantly correlate with TECI, but the composite variable of them does. This implies that the catch-up effect cannot be improved by increasing either solely the amount of R&D expenditures or the quantity of R&D organisations. Rather, the catch-up effect of Korean regions can increase only if the quantity of R&D organisations increases when the amount of R&D expenditures increases over time.

CONCLUSION

This study used non-parametric techniques to measure the R&D efficiency of fifteen Korean regions for 2005–2009 from static and dynamic perspectives. It analysed the status of Korean regions in terms of efficiency, region classification, and strategic directions for improvement in R&D efficiency. Major findings are as follows.

- The appearance of three efficient regions and twelve inefficient regions clearly indicates an interregional disparity in terms of static R&D efficiency.
- Because six regions are increasing in productivity and nine regions are decreasing in productivity, it seems that there is an imbalance in scientific and technological advancement across the regions from a dynamic R&D efficiency perspective.
- The absence of leading regions is potentially worrying, since it is such regions, which are efficient in both a static and a dynamic sense, that could drive the overall development of the country as well as serve as benchmarks for other regions.
- While technological capacity improved on the national scale, the majority of Korean regions suffered from a decrease in R&D productivity over time that was largely attributable to a decrease

in the catch-up effect.

Through exploitative strategies, Korean regions can enhance the catching-up to best practice in order to reach the efficiency frontier. Direct technical imports and complementary R&D to intensify absorptive capacity would be helpful in bridging the interregional gap in R&D efficiency and strengthen the entire country's scientific and technological competitiveness. Policy interventions to grow the quantity of GRIs on a regional scale and to rev up the quantity of industrial R&D organisations under the financial constraint are expected to lead to the improvement of the catch-up effect.

In spite of these important findings, this study has some limitations, which suggest new avenues for future studies. First, because of the lack of access to long-term historical data, this study investigated the regional R&D patterns for only five years. Longer time series data may provide more comprehensive guidance for mid- and long-term regional R&D policy planning. Second, other intermediate variables should be considered within the regional knowledge production environments. Such factors (e.g. types of R&D performers, regional strategic industries, and R&D stages) can provide multifaceted insights into regional R&D phenomena. Third, the scope of this study was restricted to Korea. A cross-country analysis using the Organization for Economic Cooperation and Development (OECD) members may aid in capturing the position of Korean regions on the supranational scale. Lastly, investigations of the effect of other factors (e.g. partner accessibility, demographic changes, and industrial shifts) on static and dynamic R&D efficiency could help clarify particular causes and specify policy implications. Despite these limitations, this study highlights one of key issues regarding balanced regional development of Korea by specifically evaluating the differences in the regional R&D efficiencies. Methodologically, the nonparametric quantitative methods used in this study illustrate a possible approach for comparing interregional innovation performance on a national scale for countries with a small number of regions.

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Table 1. Key statistics of Korean regions

No.	Region	Type	GRDP in 2009 ^c (billion KRW ^d)	Area in 2009 (km ²)	Population in 2007 (000)	Map
1	Seoul	Special city	237,594	605	10,039	
2	Busan	Metropolitan city	51,349	766	3,446	
3	Daegu	Metropolitan city	30,151	884	2,431	
4	Incheon	Metropolitan city	47,479	1,027	2,661	
5	Gwangju	Metropolitan city	20,671	501	1,450	
6	Daejeon	Metropolitan city	21,763	540	1,515	
7	Ulsan	Metropolitan city	43,191	1,058	1,094	
8	Gyeonggi	Province	203,627	10,136	11,637	
9	Gangwon	Province	25,360	16,613	1,443	
10	Chungcheongbuk	Province	31,079	7,433	1,479	
11	Chungcheongnam ^a	Province	67,055	8,629	1,959	
12	Jeollabuk	Province	28,471	8,061	1,703	
13	Jeollanam	Province	48,008	12,233	1,740	
14	Gyeongsangbuk ^b	Province	66,239	19,029	2,592	
15	Gyeongsangnam	Province	68,383	10,532	3,141	
16	Jeju	Special self-governing province	8,893	1,849	547	

Notes: Compiled from Statistics Korea (<http://www.kostat.go.kr/eng/>), last accessed on 5th October, 2011; ^a Daejeon excluded; ^b Daegu excluded; ^c Gross Regional Domestic Product, fixed base year 2005; ^d Korean currency unit: won

Table 2. Inputs and outputs in evaluating regional R&D efficiency in Korea

Indicator		Data source	Region	Year					
				2005	2006	2007	2008	2009	2010
Input	Amount of R&D expenditure (after inflation adjustment, billion KRW)	Survey of Research and Development in Korea, MEST	Seoul	1654.59	2272.83	2473.51	1526.53	2608.66	-
			Busan	125.88	268.77	348.10	157.94	289.67	-
			Daegu	134.11	141.84	165.25	108.08	189.58	-
			Incheon	421.51	496.88	670.56	250.57	514.55	-
			Gwangju	123.40	173.46	200.91	106.46	188.18	-
			Daejeon	1042.91	1391.83	1343.94	839.92	1555.95	-
			Ulsan	132.89	245.08	141.40	87.52	140.91	-
			Gyeonggi	3433.59	5112.24	4905.86	2883.08	5558.30	-
			Gangwon	55.82	82.69	81.73	54.80	99.00	-
			Chungcheongbuk	142.84	210.54	239.37	136.90	223.42	-
			Chungcheongnam	389.20	529.68	601.88	367.13	759.33	-
			Jeollabuk	92.95	121.64	153.15	130.94	176.22	-
			Jeollanam	61.59	104.73	94.40	69.94	139.22	-
			Gyeongsangbuk	460.05	706.23	555.88	300.12	562.42	-
			Gyeongsangnam	343.83	548.84	514.53	302.99	501.41	-
Output	Number of PCT applications (count)	WIPO website (http://www.wipo.int)	Seoul	-	2,960.00	3,432.00	4,151.00	4,189.00	4,742.00
			Busan	-	256.00	340.00	362.00	289.00	389.00
			Daegu	-	179.00	185.00	275.00	264.00	321.00
			Incheon	-	299.00	347.00	465.00	491.00	557.00
			Gwangju	-	162.00	162.00	210.00	274.00	262.00
			Daejeon	-	770.00	992.00	1,330.00	1,370.00	1,140.00
			Ulsan	-	40.00	58.00	85.00	101.00	125.00
			Gyeonggi	-	2,352.00	2,971.00	3,421.00	3,491.00	4,201.00
			Gangwon	-	60.00	74.00	108.00	106.00	106.00
			Chungcheongbuk	-	109.00	152.00	232.00	203.00	225.00
			Chungcheongnam	-	164.00	197.00	256.00	270.00	327.00
			Jeollabuk	-	79.00	76.00	94.00	97.00	158.00
			Jeollanam	-	67.00	70.00	92.00	98.00	82.00
			Gyeongsangbuk	-	220.00	297.00	482.00	509.00	411.00
			Gyeongsangnam	-	337.00	325.00	483.00	388.00	449.00
	Number of SCIE publications (count)	SCI Database Analysis, MEST	Seoul	-	17,986.00	19,227.00	19,421.00	23,661.00	27,009.00
			Busan	-	2,530.00	2,661.00	2,843.00	3,553.00	3,791.00
			Daegu	-	1,731.00	1,829.00	1,956.00	2,470.00	2,865.00
			Incheon	-	1,664.00	1,793.00	1,955.00	2,218.00	2,528.00
			Gwangju	-	2,225.00	2,103.00	2,300.00	2,863.00	3,077.00
			Daejeon	-	7,817.00	7,389.00	7,640.00	8,819.00	10,202.00
			Ulsan	-	305.00	358.00	407.00	598.00	844.00
			Gyeonggi	-	7,448.00	7,818.00	8,478.00	10,465.00	12,150.00
			Gangwon	-	1,195.00	1,367.00	1,459.00	1,665.00	2,186.00
			Chungcheongbuk	-	1,061.00	1,192.00	1,291.00	1,479.00	1,802.00
			Chungcheongnam	-	1,297.00	1,370.00	1,440.00	1,952.00	2,338.00
			Jeollabuk	-	1,545.00	1,560.00	1,826.00	2,177.00	2,522.00
			Jeollanam	-	543.00	510.00	546.00	735.00	837.00
			Gyeongsangbuk	-	2,476.00	2,700.00	2,776.00	3,389.00	3,645.00
			Gyeongsangnam	-	1,663.00	1,944.00	1,977.00	2,645.00	2,968.00

Table 3. Static R&D super-efficiency and R&D productivity change by region in Korea for 2005–2009

Region	Static R&D efficiency		R&D productivity change	
	(DEA super-efficiency)		(MPI)	
	Score	Ranking	Score	Ranking
Seoul	1.116	2	0.988	8
Busan	0.849	5	1.354	2
Daegu	1.029	3	0.803	11
Incheon	0.496	10	0.655	14
Gwangju	0.916	4	1.055	5
Daejeon	0.524	8	1.050	6
Ulsan	0.302	14	0.343	15
Gyeonggi	0.406	13	0.906	10
Gangwon	1.327	1	0.991	7
Chungcheongbuk	0.557	7	0.780	12
Chungcheongnam	0.260	15	0.987	9
Jeollabuk	0.678	6	1.108	3
Jeollanam	0.507	9	1.750	1
Gyeongsangbuk	0.434	12	0.733	13
Gyeongsangnam	0.487	11	1.083	4

Table 4. Technical efficiency change and technical change by region in Korea for 2005–2009

Region	R&D productivity change		Catch-up effect		Frontier-shift effect	
	(MPI)		(TECI)		(TCI)	
	Score	Ranking	Score	Ranking	Score	Ranking
Seoul ^a	0.988	8	0.880	7	1.124	10
Busan	1.354	2	1.211	2	1.118	13
Daegu ^c	0.803	11	0.656	11	1.223	2
Incheon	0.655	14	0.586	14	1.119	11
Gwangju	1.055	5	0.924	6	1.141	8
Daejeon	1.050	6	0.858	8	1.223	1
Ulsan	0.343	15	0.296	15	1.157	7
Gyeonggi	0.906	10	0.810	10	1.119	12
Gangwon ^c	0.991	7	1.000	4	0.991	15
Chungcheongbuk	0.780	12	0.643	12	1.213	3
Chungcheongnam ^a	0.987	9	0.847	9	1.165	6
Jeollabuk	1.108	3	1.088	3	1.019	14
Jeollanam	1.750	1	1.446	1	1.211	4
Gyeongsangbuk ^b	0.733	13	0.612	13	1.197	5
Gyeongsangnam	1.083	4	0.958	5	1.130	9
Geometric means across regions	0.920		0.806		1.141	

^a efficient region

Table 5. Results of Kendall's coefficient of concordance test

	R&D productivity change (MPI)	Catch-up effect (TECI)	Frontier-shift effect (TCI)
R&D productivity change (MPI)		.924***	-.143
Catch-up effect (TECI)	.924***		-.219
Frontier-shift effect (TCI)	-.143	-.219	

Table 6. Trends of Malmquist productivity index, technical efficiency change, and technical change by region in Korea for 2005–2009

Region	R&D productivity change (MPI)					Catch-up effect (TECI)					Frontier-shift effect (TCI)				
Year	2005- 2006	2006- 2007	2007- 2008	2008- 2009	Geometric means across years	2005- 2006	2006- 2007	2007- 2008	2008- 2009	Geometric means across years	2005- 2006	2006- 2007	2007- 2008	2008- 2009	Geometric means across years
Seoul ^c	1.088	0.950	0.782	1.228	0.998	0.880	1.000	1.000	1.000	0.968	1.237	0.950	0.782	1.228	1.031
Busan	1.332	1.215	0.563	1.364	1.056	1.103	1.408	0.811	0.961	1.049	1.207	0.863	0.694	1.419	1.006
Daegu ^c	1.011	0.934	0.813	1.204	0.981	0.656	1.000	1.069	0.936	0.900	1.541	0.934	0.761	1.287	1.090
Incheon	1.016	1.008	0.382	1.743	0.909	0.754	1.119	0.579	1.199	0.875	1.347	0.901	0.661	1.454	1.039
Gwangju	1.332	0.971	0.551	1.350	0.991	1.039	1.149	0.726	1.067	0.981	1.282	0.845	0.760	1.266	1.010
Daejeon	1.099	0.749	0.603	2.129	1.014	0.737	0.852	0.985	1.387	0.962	1.490	0.880	0.612	1.535	1.054
Ulsan	1.305	0.399	0.519	1.281	0.767	0.925	0.447	0.849	0.845	0.738	1.410	0.893	0.611	1.517	1.040
Gyeonggi	1.178	0.833	0.576	1.602	0.976	0.875	0.926	0.942	1.061	0.949	1.347	0.900	0.612	1.510	1.028
Gangwon ^c	1.135	0.962	0.782	1.173	1.001	1.000	1.000	1.000	1.000	1.000	1.135	0.962	0.782	1.173	1.001
Chungcheongbuk	1.090	0.788	0.642	1.454	0.947	0.725	0.893	1.048	0.948	0.896	1.504	0.883	0.613	1.534	1.057
Chungcheongnam ^a	1.152	0.898	0.569	1.710	1.002	0.801	1.017	0.929	1.118	0.959	1.437	0.883	0.613	1.529	1.044
Jeollabuk	1.293	1.076	0.717	1.106	1.025	1.002	1.162	1.221	0.766	1.021	1.291	0.926	0.588	1.445	1.004
Jeollanam	1.651	0.706	0.681	2.232	1.154	1.138	0.806	1.114	1.415	1.097	1.450	0.876	0.612	1.577	1.052
Gyeongsangbuk ^b	1.264	0.535	0.512	2.233	0.938	0.839	0.606	0.828	1.454	0.884	1.505	0.883	0.618	1.536	1.060
Gyeongsangnam	1.644	0.637	0.725	1.435	1.021	1.212	0.711	1.180	0.943	0.989	1.356	0.896	0.614	1.522	1.032
Geometric means across regions	1.226	0.815	0.616	1.509	0.982	0.898	0.908	0.936	1.056	0.947	1.364	0.898	0.659	1.429	1.036

Figure 1. A linear illustration of a regional knowledge production function

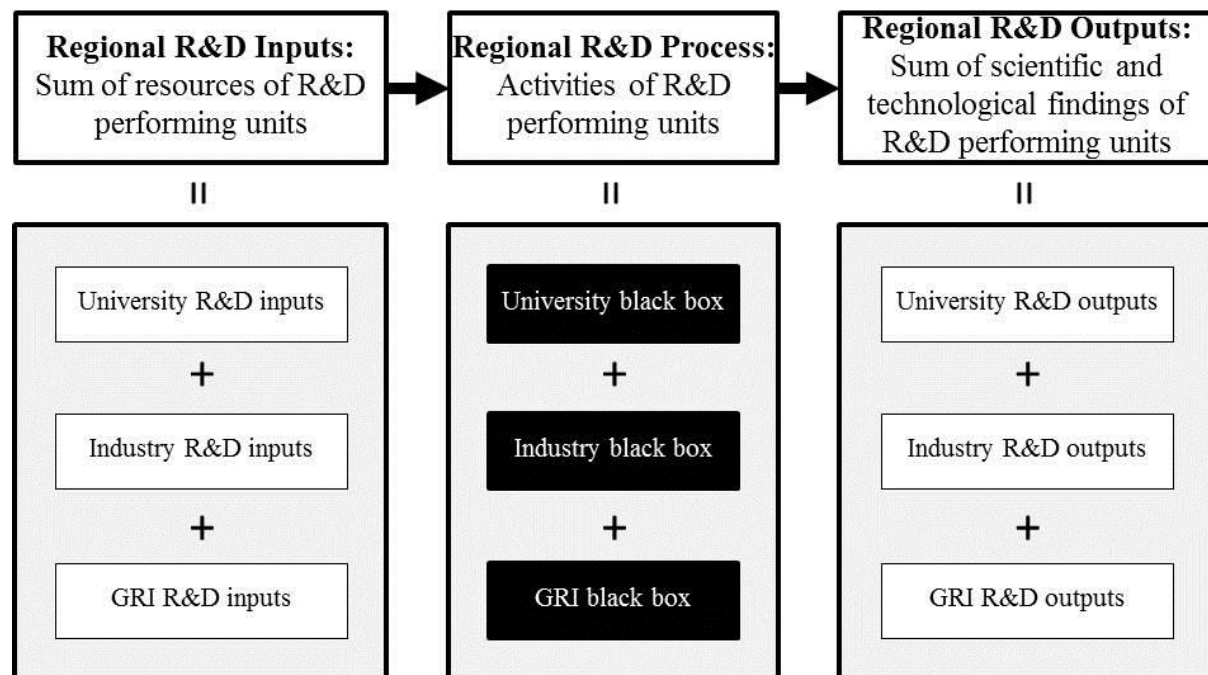


Figure 2. Regional R&D efficiency patterns

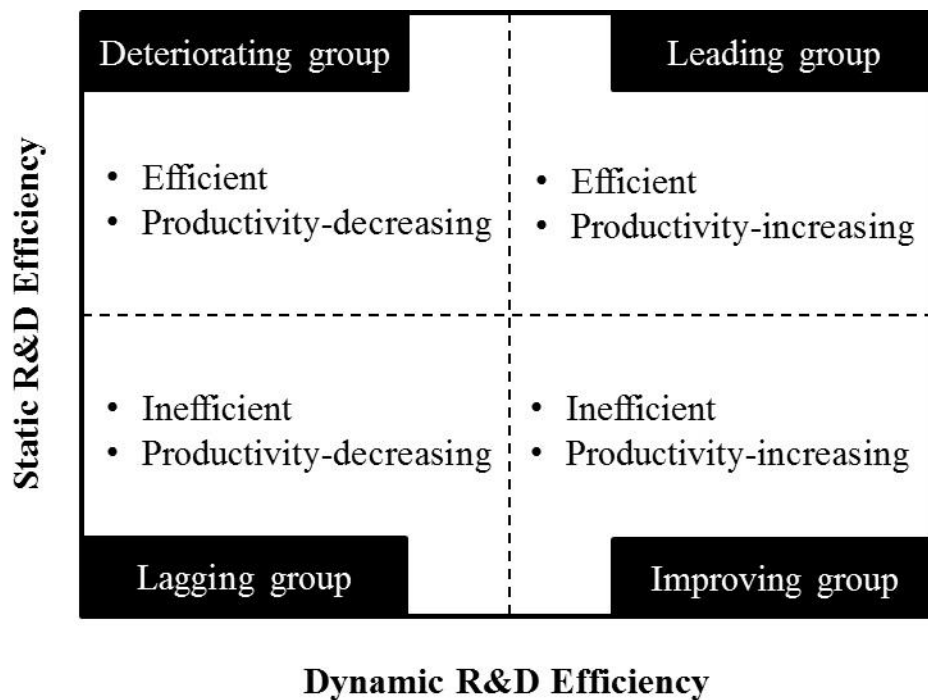


Figure 3. Positions of Korean regions. Note: Dotted lines parallel to the x-axis and y-axis indicate the threshold value that distinguishes efficient regions from inefficient ones (based on an input-oriented super-efficiency CCR-DEA model) and efficiency-increasing regions from efficiency-decreasing ones (based on an input-oriented CCR-MPI model), respectively.

